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on looking into the black box: prospects and limits in the search for mental models

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william b. rouse

nancy m. morris

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school of industrial and systems engineering
georgia institute of technology
a unit of the university system georgia
atlanta, georgia 30332

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12. PERSONAL AUTHOR(S)
William B. Rouse, Nancy M. Morris

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ON LOOKING INTO THE BLACK BOX: PROSPECTS AND LIMITS IN THE SEARCH FOR MENTAL MODELS

William B. Rouse

Center for Man-Machine Systems Research
Georgia Institute of Technology
Atlanta, Georgia 30332

Nancy M. Morris

Search Technology, Inc.
25B Technology Park/Atlanta
Norcross, Georgia 30092

ABSTRACT

The notion that humans have "mental models" of the systems with which they interact is a ubiquitous construct in many domains of study. This paper reviews the ways in which different domains define mental models, characterize the purposes of such models, and attempt to identify the forms, structures, and parameters of models. The resulting distinctions among domains are described in terms of two dimensions: 1) nature of model manipulation, and 2) level of behavioral discretion. A variety of salient issues emerge, including accessibility of mental models, forms and content of representation, nature of expertise, cue utilization, and, of most importance, instructional issues. Prospects for dealing with these issues are considered, as well as fundamental limits to identifying or capturing humans' "true" mental models.

INTRODUCTION

It is a common assertion that humans have "mental models" of the systems with which they interact. In fact, it is difficult to explain many aspects of human behavior without resorting to a construct such as mental models [Conant and Ashby, 1970]. However, acceptance of the logical necessity of mental models does not eliminate conceptual and practical difficulties; it simply raises a whole new set of finer-grained issues.

For example, what forms do mental models take? How does the form affect the usage of the models? Is guidance in the use of models as important as their form? How can and should designers and trainers attempt to affect humans' mental models? These really are not new questions. However, as is discussed later, once they are expressed in terms of the concept of mental models, they tend to be dealt with somewhat differently.

Further, despite many sweeping claims in the contemporary literature, available answers to the above questions are rather inadequate. There are prospects for improving this situation. However, there also are limits; the "black box" of human mental models will never be completely transparent. This paper considers these prospects and limits.

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Further, despite many sweeping claims in the contemporary literature, available answers to the above questions are rather inadequate. There are prospects for improving this situation. However, there also are limits; the "black box" of human mental models will never be completely transparent. This paper considers these prospects and limits.

To place the arguments advanced in this paper in

perspective, several points of view with regard to mental models are first reviewed. Alternative definitions, purposes, and taxonomies are discussed in the context of a variety of behavioral domains. This leads to a discussion of differences among domains, particularly in terms of methods for identifying the form, structure, parameters, etc. of mental models. From this discussion emerges a key set of issues, which initially are discussed in general. Discussion then focuses on issues specifically associated with instruction (i.e., fostering the creation of mental models). Finally, fundamental limits in the search for mental models are considered.

DEFINITIONS

While the phrase "mental models" is ubiquitous in the literature, there are surprisingly few explicit definitions provided. This most likely reflects the extent to which the concept has come to be completely acceptable on an almost intuitive basis. Nevertheless, it is interesting to consider the few formal definitions that have been espoused.

The manual control community has traditionally focused on skilled, psychomotor performance. More recently, the term "manual" is giving way to "supervisory" in recognition of the fact that the human's role is increasingly becoming one of monitoring automatically-controlled systems for the purpose of

detecting, diagnosing, and compensating for system failures [Sheridan and Johannsen, 1976; Rasmussen and Rouse, 1981]. In reviewing the use of the concept of mental models in this domain, Veldhuyzen and Stassen [1977] conclude that a human's mental model includes knowledge about the system to be controlled, knowledge about the properties of disturbances likely to act on the system, and knowledge about the criteria, strategies, etc. associated with the control task. In a recent, and more circumspect, discussion of research in this area, Wickens [1984] refers to the concept of a mental model as a "hypothetical construct" to account for human behavior in sampling, scanning, planning, etc. Jagacinski and Miller [1978], also working in manual control, define mental models as special cases of "schema," a fairly well-accepted psychological notion of how skilled performance is organized (see Wickens [1984]).

While the manual control community has been blithely using the mental models concept for at least twenty years, cognitive psychology has only recently embraced this notion. This acceptance is clearest in the area of "cognitive science," which is basically the result of a liaison between cognitive psychology and computer science or artificial intelligence. This relatively new community of researchers has recently produced an edited book on mental models [Gentner and Stevens, 1983].

In contrast to manual and supervisory control where mental

models serve as assumptions which allow calculations of expected control performance, research in cognitive science tends to focus directly on mental models, particularly in terms of the ways in which humans understand systems. Norman [1983] characterizes this understanding as messy, sloppy, incomplete, and indistinct knowledge structures. Lehner and his colleagues [1984] have asserted that humans' mental models of a particular class of computer programs (i.e., expert systems) include understanding that: 1) the program's knowledge is encoded in rules, 2) rules are organized in the program in terms of a network of relationships, and 3) explanatory traces of program behavior involve chaining along this network. Definitions that emphasize somewhat narrower behavioral domains include topologies of device models [Brown and deKleer, 1981; deKleer and Brown, 1983] and collections of autonomous objects [Williams, et al., 1983]. Thus, it can be seen that definitions within the cognitive science community range from broad and intentionally amorphous generalizations to specific and somewhat esoteric constructs.

A very significant difficulty with the phrase "mental models" involves how one should differentiate this concept from that of "knowledge" in general. Does this phrase reflect the common tendancies of young sciences to re-label everyday phenomena? Certainly cognitive science and especially artificial intelligence appear to have penchants for coining terminology. Nevertheless, in this case, it appears to be reasonable to employ

the concept of mental models to connote special types of knowledge. This becomes clear when one considers the purposes that mental models are supposed to serve.

PURPOSES

The above discussion tended to emphasize the differences in perspectives of researchers in manual/supervisory control and cognitive science. These differences in definitions and terminology are considerably lessened once one considers purposes.

Veldhuyzen and Stassen [1977], in their review of the use of the mental model concept in manual control, conclude that mental models provide the basis for estimating the "state" of the system (i.e., estimating state variables that are not directly displayed), developing and adopting control strategies, selecting proper control actions, determining whether or not actions led to desired results, and understanding unexpected phenomena that occur as the task progresses. This conclusion, in effect, asserts that mental models are the basis for all aspects of manual control. Such a sweeping assertion can lead one to surmise that "mental models" are synonymous with "knowledge" in general.

In fact, Veldhuyzen and Stassen appear to be correct in the

sense that the phrase mental models <u>is</u> <u>used</u> in this way, especially in the manual/supervisory control community. However, this is not the way the phrase <u>should be used</u>. More precision is needed; otherwise, there is a great risk that the result of research in this area will simply be that, "humans have to know something in order to perform their tasks." Clearly, this result will not be a great stride for science.

Rasmussen [1979, 1983], also working within the domain of supervisory control, limits the range of purposes of mental models. He asserts that mental models are for predicting future events, finding causes of observed events, and determining appropriate actions to cause changes [Rasmussen, 1979]. He also includes the use of mental models for performing "internal" experiments [Rasmussen, 1983], or what physicists refer to as "thought" or "Gedanken" experiments [Zukav, 1979].

Alexander [1964] discusses the "mental pictures" employed by engineering and architectural designers. These pictures are defined quite broadly in terms of contexts (problem definitions) and forms (alternative solutions). Hence, the purposes of designers' mental pictures or models are viewed as much more encompassing than the models discussed in the supervisory control arena. This difference in scope most likely reflects inherent differences between open-ended tasks such as design and well-defined tasks like supervisory control.

Within the cognitive science domain, Williams and his colleagues [1983] claim the purposes of mental models to be predicting and explaining system behavior and serving as mnemonic devices for remembering relationships and events. Evidencing a more traditional psychological point of view, Wickens [1984] reports that mental models are constructs used by researchers to explain display sampling and scanning, formulating of plans, and translating of goals into actions. He also suggests that mental models are sources of humans' expectations.

The intersection of the various points of view outlined in this section leads to a fairly clear set of purposes for mental models. The common themes are <u>describing</u>, <u>explaining</u>, and <u>predicting</u>, regardless of whether the human is performing internal experiments, scanning displays, or executing control actions. These three terms can be combined with a modification of Rasmussen's taxonomy of mental models [Rasmussen, 1979] to yield the integrated view of the purposes of mental models shown in Figure 1.

Based on this figure, a functional definition of mental models can be proposed: mental models are the mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future system states. It is important to emphasize that this definition does not differentiate between

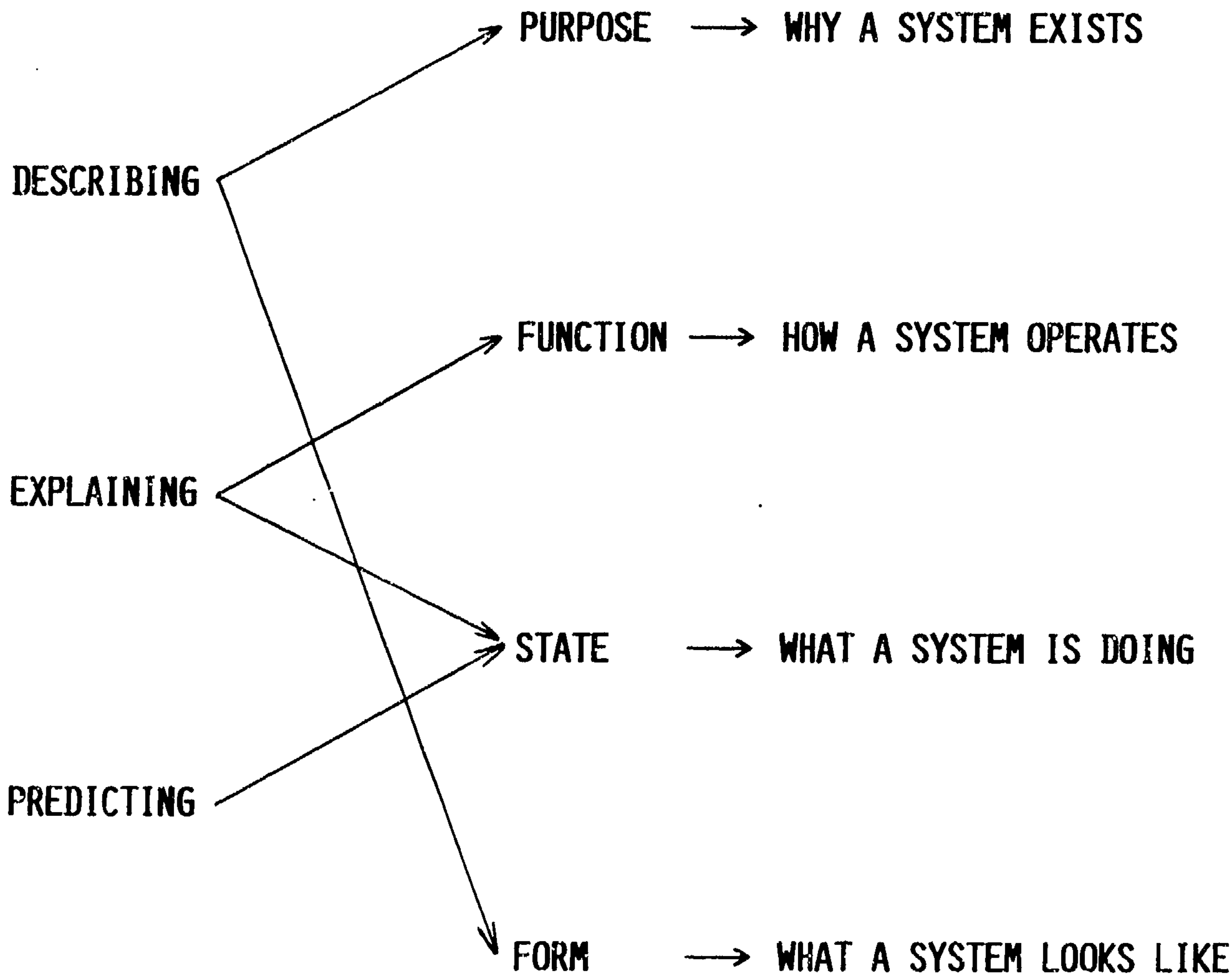

FIGURE 1. PURPOSES OF MENTAL MODELS

knowledge that is simply retrieved and knowledge that involves some type of calculation. Thus, humans' mental models are not necessarily computational models.

It was noted earlier that a models = knowledge definition should be avoided if the mental models construct is to have any real utility. The above definition does not eliminate this problem, which serves to underscore the possibly marginal value of the construct. Nevertheless, the proposed definition does specify particular types of knowledge and the purposes for which this knowledge is used. This level of specificity is sufficient to enable a meaningful inquiry into the nature of mental models.

IDENTIFICATION

Given the above functional definition of mental models, one can then reasonably consider how these mechanisms might be identified. In other words, what forms, structures, parameters, etc. are associated with mental models of particular individuals for specific task situations? There are a variety of approaches to these types of question.

Inferring Characteristics Via Empirical Study

Perhaps the most traditional approach to the study of mental models is the use of experimental methods to infer the

characteristics of models. This approach is the stock in trade of experimental psychology. An excellent example of this approach is the work of Kessel and Wickens [1982] who studied the impact of training (manual control vs. monitoring of automatic control) on subsequent monitoring performance. They found that the cue utilization abilities fostered by manual control training were more successfully transferred to subsequent monitoring performance than training based on monitoring of automatic control. Despite the fact that proprioceptive channels (due to control stick movements) were no longer available in the transfer conditions, manual training was clearly superior. Based on this finding, the investigators inferred that the mental models developed in the two conditions were different in that the type of information employed in monitoring depended on the type of training.

While inference via empirical study provides evidence for effects of various independent variables on characteristics of mental models, these types of result provide, at best, only indirect insights into the form (e.g., spatial vs. verbal) and structure (e.g., hierarchical vs. planar) of mental models. This is due to the likelihood that access and manipulation of models are confounded with perception and response execution; interaction among these three stages of information processing can limit the precision of conclusions.

Empirical Modeling

In situations where perception and response execution are unlikely to interact with model manipulation, empirical modeling may be possible. This approach involves algorithmically identifying the relationship between humans' observations and subsequent actions. If it can be assumed that humans actually perceive what is displayed and response execution is very simple, then techniques such as regression can be used to identify input-output relationships. From these relationships, the structure and parameters of mental models can be inferred. Jagacinski and Miller [1978] employed this approach for a "bang-bang" time-optimal manual control task where regression on subjects' "switching curves" allowed inferences about mental models. Several investigators have studied the relationships between humans' explicit predictions of future system states and currently displayed states, using regression or time-series models to identify input-output relationships [Rouse, 1977; van Bussel, 1980; van Heusden, 1980]. All four of the above studies resulted in hypothesized mental models that differed systematically from the "true" model of the system involved.

It is worth noting that related approaches have been employed in a variety of studies of human judgement. Anderson's "cognitive algebra" and Hammond's "policy capturing" are two notable examples; a thorough review of these and other efforts

is provided by Hammond and his colleagues [1980]. These studies of the combining of cues to form judgements are rather different than the types of task discussed thus far in this paper, in that the combination rules that are identified do not necessarily directly relate to any explicit model of the system. Nevertheless, the whole issue of cue utilization is very important and is discussed further later in this paper.

Analytical Modeling

There are very few tasks where empirical modeling is appropriate. For most tasks, the input-output relationships identified would be very likely to be confounded with characteristics of displays and controls, as well as subjects' interpretations of performance criteria. Analytical modeling is a common approach to these types of task, particularly in the manual/supervisory control community.

Analytical modeling involves using available theory and data to formulate assumptions about the form, structure, and perhaps parameters of mental models for particular tasks. Based on these assumptions, human performance (e.g., RMS tracking error) is calculated or computed analytically and compared to empirical performance data. A common practice is to adjust the parameters of the assumed mental model in order to minimize differences between the analytical and empirical performance metrics. If the

resulting differences are fairly small, one can conclude that the assumed mental model is a reasonable approximation for the purpose of predicting the performance metric of interest. In contrast, one cannot safely conclude that one has identified the "real" mental model. Unfortunately, this leap, perhaps of faith, occurs not infrequently.

The nature of some domains virtually dictates the use of analytical modeling. Neural information processing is a good example where basic knowledge of neuron behavior is used to synthesize network models. The overall behaviors of these network models are analytically determined and compared to empirical results of basic psychological studies [Anderson, 1983]. The complexity of the neural system is such that a purely empirical approach is simply not feasible.

As noted earlier, analytical modeling is quite common in the manual/supervisory control domain. Because of the very constrained nature of many manual control environments (i.e., the human must adapt to the task in order to perform acceptably), a common assumption is that humans' mental models are perfect relative to the real system (e.g., [Kleinman, et al., 1971]). However, for tasks involving only monitoring [Smallwood, 1967; Sheridan, 1970], especially when apparent discontinuities occur in the state trajectory [Cagalayan and Baron, 1981], imperfect models are often assumed. Imperfect mental models are also

assumed for tasks that involve slowly-responding systems such as ships and process plants [Veldhuyzen and Stassen, 1977], where the human has much greater discretion in terms of the timing and magnitude of control actions.

The assumption of an imperfect mental model can be problematic from an analytical point of view. If a perfect mental model can be assumed, one need only perform an engineering analysis of the system of interest to identify the model. In a sense, there is only one choice. In contrast, there is an infinity of alternative imperfect models, and justifying the choice of any particular alternative can be difficult. Of course, if one's objective is solely the prediction of some overall performance metric, this difficulty may be minor. However, the fact that one is able to "match" such an overall metric does <u>not</u> imply that one can reasonably conclude that the imperfections assumed in the analytical model are identical to the actual imperfections inherent in the human's mental model.

Direct Inquiry

Perhaps an obvious alternative to the somewhat indirect methods of identification discussed above is simply to ask people about their mental models. Introspection, in a variety of forms, was a common approach to psychological research in the 19th century, particularly in Europe. However, the behaviorist

movement of Watson [1914] and later Skinner [1938] almost completely divested this approach of any credibility it may have had within experimental psychology. Fortunately, the last two decades have produced a substantial softening of the strict behaviorist perspective. Nevertheless, psychologists' yearning to be like physicists still persists to some extent, despite fundamental and irreducible differences between the two domains of study [Rouse, 1982].

An approach to introspection that has gained substantial currency of late is the verbal protocol, which is simply a transcript of a human "thinking aloud" as he or she performs a task. Insightful analyses of verbal protocols have been performed for troubleshooting [Rasmussen and Jensen, 1974], process control [Bainbridge, 1979], device understanding [Williams, et al., 1983], problem solving in elementary physics [Gentner and Gentner, 1983], and various game-like tasks [Newell and Simon, 1972]. In the cognitive science domain, there are many examples of verbal protocols serving as the "data" from experiments; see [Gentner and Stevens, 1983].

While there are strong advocates of this approach in the manual/supervisory control community [Bainbridge, 1979; Rasmussen, 1979, 1983] as well as the cognitive science community [Newell and Simon, 1972; Ericsson and Simon, 1980, 1984], there are also more circumspect views [Nisbett and Wilson, 1977].

Certainly, what humans say they are thinking about or intend to do is interesting and of value. However, verbalization of a non-verbal (e.g., spatial or pictorial) image may result in severe distortions and biases. Further, verbal protocols provide, at best, information about what humans are thinking about, but little direct information about how they are thinking (i.e., about the underlying information processing). Therefore, it seems prudent to view verbal protocols as quite useful, but far from conclusive. As a result, such data may be more useful for generating hypotheses for subsequent experimentation rather than as a primary means for testing hypotheses (unless, of course, the hypotheses only address the "what" of thinking).

Another approach to direct identification of mental models is interviews and/or questionnaires. In general, this approach is quite different from verbal protocols. However, in some cases, the only difference between this approach and verbal protocols is the fact that the inquiry does not occur as the task is performed. Studies of air traffic control by Falzon [1981] and Whitfield and Jackson [1982], and of marine navigation by Hutchins [1983], are of this type.

In contrast, interviews and/or questionnaires concerning preferences or judgements are not necessarily task-oriented. In such cases, there is really no reason to make inquiries during task performance. An excellent example of this type of situation

is the study of "mental maps" by Gould and White [1974], where the concern was with geographical perceptions and preferences. (Wickens [1984, pp. 189-192] reviews a variety of studies of how humans' mental representations of imagined maps tend to be distorted.)

As an interesting aside, the above observations on direct inquiry have important implications for the design of "expert systems." Succinctly, experts may not be able to verbalize their expertise. Perhaps worse, their verbalizations may reflect what they expect is wanted by the inquirer rather than how they actually perform. An example of evidence of this phenomenon is a recent study of process control operators whose explanations of what they thought they would (or perhaps should) do were at variance with their actual behaviors [Morris and Rouse, 1985; Knaeuper and Rouse, 1985].

Summary

Reconsidering all of the approaches to identification discussed in this section, it is clear that each type of approach has substantial advantages for some types of task, but also important weaknesses. Further, while employing multiple approaches can compensate for these weaknesses to an extent, the possibility of totally "capturing" the mental model is rather remote. This is, in part, due to the great likelihood that a

mental model does not exist as a static entity having only a single form.

TAXONOMIES

It is fairly easy to accept the assertion that any particular phenomenon can be thought of in a variety of ways. For example, one can think of an automobile as a collection of electromechanical elements that convert chemical energy of fuel to mechanical energy in terms of motion. In contrast, one can view an automobile as a sleek, sculptured, and powerful extension of one's persona. Both of these "mental models" involve the same physical entity. However, the verbal protocols produced for these two models of an automobile would differ in rather dramatic ways. This would be the case even if the two protocols were produced by the same individual.

As noted earlier, Rasmussen [1979] has developed a taxonomy of alternative mental models of systems. His taxonomy moves from concrete to abstract perspectives in terms of five types of model: 1) physical form, 2) physical function, 3) functional structure, 4) abstract function, and 5) functional meaning or purpose. Thus, roughly speaking, a system can be viewed as what it looks like, how it functions, or why it exists. All of these views are "correct" and of value for answering a variety of questions about a system.

Norman [1983] uses the word "conceptualization" to characterize researchers' models of humans' mental models. This characterization serves to emphasize the difficulty of studying mental models in that one is basically searching for approximations of approximations of reality [Cohen and Murphy, 1984], a process that can be viewed as akin to estimating the variance of the variance in statistical modeling.

The conceptualizations chosen by researchers tend to reflect their methodological backgrounds and the way in which they assume humans are likely to view the systems of interest. Assumptions about how people view systems are, of course, also likely to be affected by researchers' backgrounds (e.g., engineers may think that operators and maintainers view systems from an engineering perspective). Thus, researchers' mental models affect their conceptualization of other humans' mental models; to avoid getting sidetracked by this issue, it is not pursued further until a later section of this paper.

A practical implication of this phenomenon is that it is quite natural to taxonomize mental models in terms of conceptualizations. In reviewing how researchers have approached human detection and diagnosis of system failures, Rasmussen and Rouse [1981] contrast conceptualizations involving differential equations, functional block diagrams, and "snapshots" of physical form as examples of different ways that various researchers view

similar problems. Beyond differences in conceptualizations dictated by researchers' natural inclinations, there are important, and hopefully more substantial, effects of differences in how mental models are used.

Young [1983] has suggested a range of uses of mental models. For example, a mental model might be used as a way of describing a device independent of its usage. Another use of a mental model of a device might be to represent the input-output relationships associated with typical uses of the device. Yet another use of a mental model of a device is as a means of understanding an analogous device (e.g., a VDU is like a typewriter).

The clear implication of such usage-oriented perspectives is that humans' mental models of a system (e.g., within Rasmussen's taxonomy), and the most appropriate conceptualizations of these models, depend upon the tasks to be performed. If the system is used in multiple ways (e.g., the automobile example noted earlier), then multiple mental models are likely to be developed.

Therefore, a taxonomy that is purely system oriented (i.e., task independent), will be, at best, inadequate; a behavior-oriented framework is also needed. Of course, approaching mental models, or cognition in general, from a behavior or performance point of view is the norm in experimental psychology. Taxonomic efforts in this discipline tend to produce

attributes-oriented characterizations for particular tasks. For example, Wickens [1984] discusses specificity and code of representation as attributes of mental models in process control.

From the foregoing discussion, it is clear that efforts to develop taxonomies of mental models are heavily influenced by the domain being investigated (e.g., word processing vs. vehicle control), as well as the backgrounds of the investigators (e.g., psychology vs. engineering vs. computer science). Research in a wide variety of domains can be characterized as dealing with mental models. Thus, the literature cited in this paper includes several domains: 1) neural information processing, 2) manual control, 3) supervisory control, 4) understanding of devices (e.g., for maintenance purposes), 5) problem solving in physics, and 6) making value judgements.

While all of the research cited in these domains explicitly deals with mental models (or equivalent concepts), these efforts differ substantially in terms of conceptualizations chosen and identification methods employed. It appears that these differences can be explained by distinctions among domains along two dimensions: 1) nature of model manipulation, and 2) level of behavioral discretion. The distinctions among the various domains listed above are illustrated in terms of these two dimensions in Figure 2. (Note that "understanding of devices" appears as "system maintenance" and "using assembly

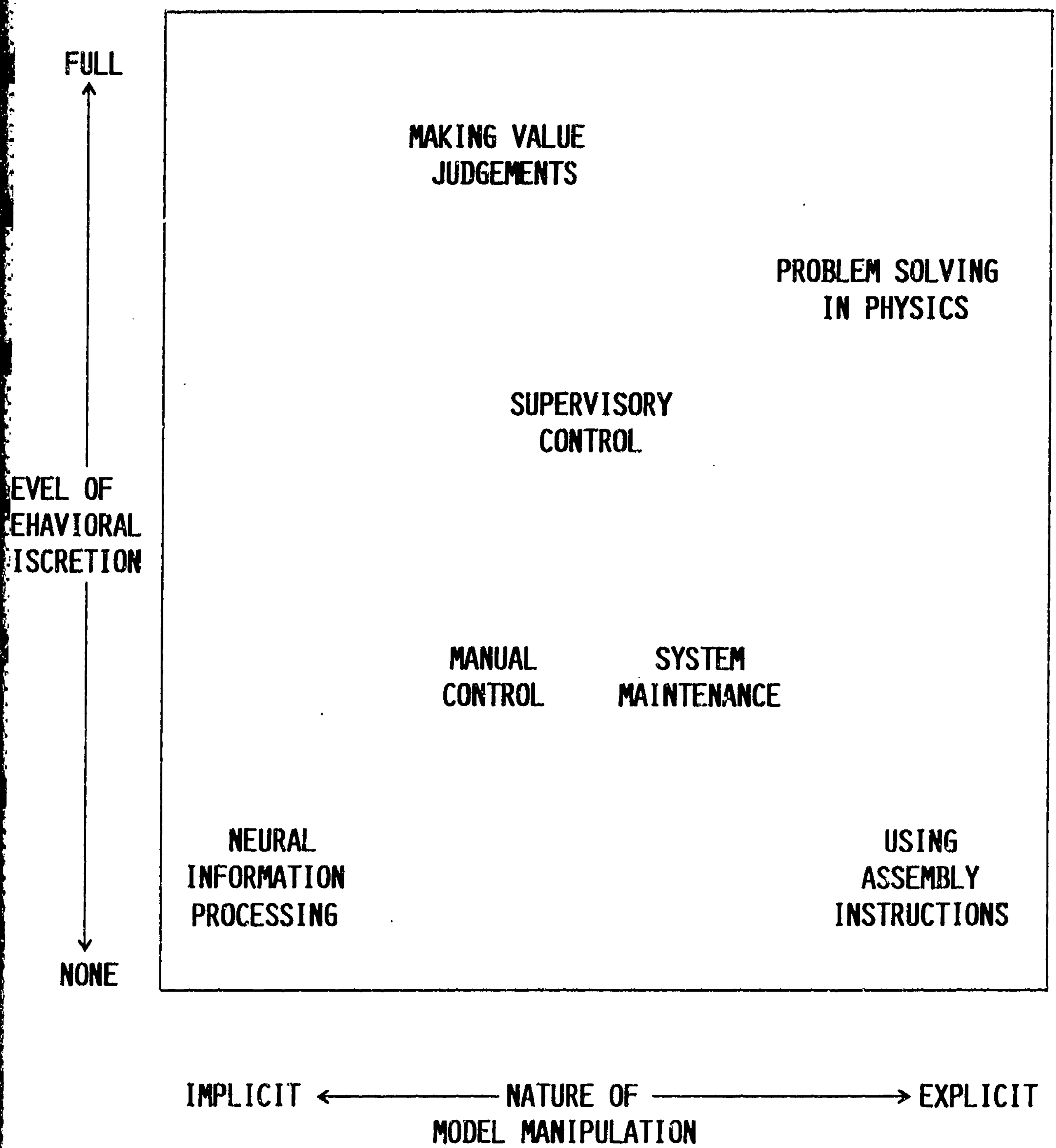

FIGURE 2. DISTINCTIONS AMONG DOMAINS

instructions.")

The <u>nature of model manipulation</u> can range from implicit to explicit, where these terms refer to whether or not a human is aware of his or her manipulation of a mental model. As an example, one is likely to be totally unaware of manipulating neural network representations in associative memory. In contrast, assembling devices or solving physics problems is likely to involve explicit manipulation of models.

An alternative point of view relative to this dimension is to consider the terms "implicit" and "explicit" as indicative of a dichotomy rather than end points on a continuum. The result is an analogy of the compiled vs. interpreted processes of Newell and Simon [1972]. One can also express this difference in terms of systems vs. applications software. The basic idea is that the "source code" for compiled processes or systems software is no longer available to the human who, therefore, cannot report on how it operates.

The <u>level of behavioral discretion</u> can range from none to full, where, as above, these terms refer to the extent that a human's behavior is a matter of choice, as opposed to being dictated by the task. At one extreme, phenomena such as neural information processing are unlikely to be discretionary. However, as tasks are more oriented toward decision making and

problem solving, opportunities for discretion are more likely. Interestingly, humans' roles in many engineering systems are tending toward tasks that involve greater discretion; the more task-dominated aspects of system operations are being increasingly automated.

While the relative placement of domains in Figure 2 is far from exact, the distinctions emphasized in this figure provide a basis for explaining methodological differences among domains. Considering identification methods, two generalizations seem reasonable.

First, inferential methods (i.e., empirical assessment, empirical modeling, and analytical modeling) tend to yield more accurate descriptions when there is little discretion. This is because the nature of the conceptualization of a mental model can be based on external environmental and organizational constraints. Since the human has little discretion, he or she can be assumed to adapt to these constraints and the resulting mental model will reflect this adaptation.

The second generalization is that verbalization methods (i.e., verbal protocols, interviews, and questionnaires) are likely to provide more appropriate descriptions when there is explicit manipulation. This is simply due to the fact that the need for explicit manipulation may result in verbalization being

a "natural" part of a task. Of course, it is also quite possible that manipulation may be explicit, but the mental model is, for example, spatial rather than verbal, or perhaps in terms of subjective images rather than objective constructs.

If accepted, these two generalizations have important implications. Most obvious is the conclusion that domains toward the upper left of Figure 2 are likely to present methodological difficulties, at least in the sense that mental models will be elusive. An example is the aforementioned research on human judgement (e.g., [Hammond, 1980]), which attempts to "capture" relationships between features observed and decisions made.

The results of such analyses indicate, at most, what is taken into account in the process of social decision making, but not how this information is processed in the context of one or more mental models. The types of situation addressed are too laden with implicit values and too open to discretion to allow mental models to be "captured" to the extent that they can be, for example, for device understanding. Studies of human judgment in the area of personal relations [Harvard, 1980] and personal geographical preferences [Gould and White, 1974] are good examples of this limitation.

Expanding upon the above notion, an overall implication of the generalizations drawn from Figure 2 is that the possible

level of specificity of conceptualizations of mental models, and perhaps even the form of conceptualizations, are limited by the location of a task domain along the nature of manipulation/level of discretion dimensions. In fact, it seems reasonable to conjecture that these limits may be fundamental. Elaboration of this conjecture is, however, delayed until a later section of this paper.

SALIENT ISSUES

From the discussion thus far, it is clear that there are a plethora of issues surrounding the topic of mental models. Many of these are relatively minor, involving terminology and inherent differences among domains. A few issues, however, appear repeatedly in the literature and are dominant in many of the domains discussed in this paper.

This section, as well as the following section, explore the nature of these issues. The discussion proceeds in the following sequence:

1. Accessibility - To what extent is it possible to "capture" individuals' mental models?

2. Forms of representation - What do mental models look like (e.g., spatial vs. verbal)?

3. Context of representation - To what extent can mental models be general rather than totally context-dependent?

4. Nature of expertise - How do the mental models of novices and experts differ?

5. Cue utilization - How are mental models affected by the cues one employs, either by choice or due to availability?

6. Instruction - How can and should training affect individuals' mental models?

The rationale underlying the ordering of these topics is to consider first the inherent nature of mental models, particularly as affected by context, expertise, and available cues, and then to focus on approaches to fostering the development of appropriate mental models.

Accessibility

As might be surmised from the foregoing discussion, the accessibility of mental models is a recurrent and important issue. While the considerations outlined earlier need not be repeated, it is of value to note a few examples where accessibility appears limited in the sense that researchers' abilities to "capture" mental models are constrained by humans' lack of abilities to verbalize their models. Van Heusden [1980] found that subjects had difficulty verbalizing how they predicted future states of time series. Whitfield and Jackson [1982] reported that air traffic controllers had difficulty verbalizing their "picture" of the state of the system. Wickens [1984] notes that models for control are less verbalizable than models for

detection and diagnosis. As noted earlier, Morris and Rouse [1985] and Knaeuper and Rouse [1985] found that subjects' answers regarding what they would (or perhaps should) do were different from what they actually did. Therefore, while the intent is not to belabor the point, an important issue concerns when verbalization is possible, reliable, and valid. (The previous discussion surrounding Figure 2 suggests how this issue might be viewed).

Forms of Representation

The accessibility of mental models, as well as their use in general, depends on their forms of representation. This issue concerns how mental models are encoded and perhaps evolve. While neural information processing approaches to this issue are emerging [Anderson, 1983], the potential of such fine-grained descriptions appears, at least at this point in time, to be limited to providing explanations of very elementary psychological phenomena rather than behavior in realistically complex tasks.

One important distinction relative to form is spatial vs. verbal. Considering humans' exquisite pattern recognition abilities, it is likely that the human information processing system is particularly adept at processing spatially-oriented information and, hence, may tend to store information in that

manner. Therefore, it seems reasonable to suggest that mental models are frequently pictorial or image-like rather than symbolic in a list-processing sense. This obviously presents difficulties when humans are asked to verbalize their models (e.g., the air traffic controllers of Whitfield and Jackson [1982]).

Even when verbal representations are likely (or at least useful), the vocabulary or "ontology" of such descriptions can be an important factor in the effectiveness of these representations for problem solving [Greeno, 1983]. An excellent example is that reported by Falzon [1982] where air traffic controllers thought of their task in terms of aircraft "separations" rather than "positions."

Another important distinction relative to form is representational vs. abstract. Rasmussen's taxonomy of mental models illustrates how any particular system can be described at various points along this dimension [Rasmussen, 1979]. Larkin [1983] distinguishes expert from novice solvers of physics problem in terms of abstract vs. representational mental models.

Context of Representation

A related issue concerns the context of representation, rather than the form, and whether it is general or specific

(e.g., general principles of physics or specific heuristics for troubleshooting a particular device). In reviewing the available evidence for process control, Wickens [1984] concludes that mental models tend to be specific. However, if specific representations are predominant, it is difficult to account for the richness of human problem solving behavior (i.e., abilities to solve novel problems). Explanations of this richess have included learning via metaphors [Carroll and Thomas, 1982], analogical problem solving [Steinberg, 1977; Gentner and Gentner, 1983; Silverman, 1983], and use of multiple models [Rasmussen, 1983].

While the issue of general vs. specific knowledge is certainly not new (e.g., [Peirce, 1877]), it is far from resolved. Part of the difficulty is inherent in the topic. Tasks and behavior are always specific. Hence, "general" phenomena are not observable. Yet, such constructs seem to be necessary to explain, for example, human behavior in unfamiliar situations [Glaser, 1984]. Given the fact that much of what is routine is increasingly being automated, leaving humans to deal with the non-routine, a recurring theme is training of humans to have general skills to deal with a wider variety and less familiar tasks. As might be expected, therefore, the general vs. specific issue is likely to continue to receive attention.

Nature of Expertise

At least a portion of the general vs. specifc debate has focused on the nature of expertise. The question of concern, within the context of this paper, is how experts' mental models differ from those of novices. Intuitively, one might think that experts simply know more than novices (i.e., have more elaborate and accurate mental models). However, experts' mental models are not just more elaborate or accurate; evidence suggests that they are fundamentally different from novices' models [Chi and Glaser, 1984; Glaser, 1984; Greeno and Simon, 1984].

Wisner and Carey [1983] have concluded that the "novice-expert shift" involves a conceptual change, rather than just refinement of the novice's perspective. As noted earlier, Larkin [1983] discusses this shift as a movement from representational to abstract models. Chase and Simon [1973], as well as Dreyfus and Dreyfus [1979], describe expertise in terms of highly-developed repertoires of pattern-oriented representations. If one accepts the conclusion that experts tend to have conceptually abstract, pattern-oriented mental models, then one must simultaneously question the accessibility of these models via verbalization methods. This has, of course, important implications for developers of "expert systems."

An interesting phenomenon related to expertise is the fact

that the shift away from novice does not necessarily imply that all naive notions are discarded. DiSessa [1982] and McCloskey [1983] found that naive, "pre-Newtonian" theories of motion were retained by students even after instruction in "correct" theories. Similarly, Clement [1983] found that the naive idea of "motion implies force" was retained even after instruction that indicated otherwise. Thus, individuals who know what is "correct" may also retain ideas that are "wrong," perhaps because their real-world (as opposed to instructional) experiences tend to be such that inconsistencies do not occur. In other words, mental models may include a bit of "baggage" remaining from earlier experiences that humans find no need to question or discard, even though this baggage may create difficulties when novel situations are encountered.

An alternative interpretation of the above results is that the subjects studied were not "experts" in the full sense of the word; otherwise, their naive notions would have been dispelled. While this position is reasonable, it runs the risk of investing in experts the non-human characteristic of always being correct. Alternatively, one can define expertise in relative terms. From this perspective, the results cited above are perhaps suggestive of the inherent limitations of expert opinion.

Cue Utilization

An issue that is often overlooked in discussion of mental models is cue utilization. In order to predict future system states or explain the current state, two things are needed: 1) one has to know what the current state is, and 2) one has to have some mechanism that emulates the process whereby the state evolves. The human's internalization of this mechanism is usually thought of as the mental model; however, the development and use of this mechanism cannot be divorced from the human's abilities to extract from the environment the cues necessary to form the state estimates upon which this mechanism operates.

An excellent example of possible confounding of cue utilization and mental models can be found in various studies of humans' abilities to predict future system states. Independent studies by Rouse [1977], van Bussel [1980], and van Heusden [1980] have concluded, via empirical modeling methods, that humans' models reflect inappropriate weightings of past system states. All three of these efforts assumed that past states were accurately observed, or at most were subject to zero-mean Gaussian observation noise.

However, despite these researchers' serious efforts to avoid it, subjects may have produced consistently biased or distorted state estimates which led them to develop what appeared to be

inappropriate mental models. For example, subjects may have looked for spatial patterns such as number of reversals or repeated subpatterns in the displayed time series rather using the "state" as the investigators had intended. If this was the case, it may have been that the mental models developed by subjects were "optimal" (i.e., the best fit) for those cues. In other words, it may have been that their cue utilization dictated the limits to the accuracy of their models.

This phenomenon has implications for explaining the impact of predictor displays. A predictor display explicitly depicts, via a model of the system, the future states of the system and has been shown to result in improved system performance [Sheridan and Ferrell, 1974, pp. 268-273]. One explanation for this improvement is that humans' mental models of the systems involved were other than perfect. Alternatively, as argued above, it could be that they simply tended to have difficulty estimating the higher-order state variables (e.g., acceleration and its derivatives).

A study by Johannsen and Govindaraj [1980] supports the latter hypothesis. They used a manual control model to assess the effects of a predictor display, which they represented solely in terms of improved cue utilization. Experimental data supported their formulation, although their study was designed for purposes other than providing a definitive test of the cue

utilization vs. imperfect mental model issue.

Increasing levels of automation in engineering systems have led to a variety of studies of the impact on human performance of manually controlling vs. monitoring of automatic controls in tasks such as failure detection. Kessel and Wickens [1982] found that subjects trained in failure detection while manually controlling subsequently produced better failure detection performance when monitoring an automatically controlled system. They concluded that training that included manual control leads to improved cue utilization. Ephrath and Young [1981] reach what at first glance appears to be almost the opposite conclusion but, upon closer inspection, mainly serves to illustrate the subtleties of the issue. (For example, the value of information is related to the human information processing resources required to utilize the information.) In a rather different study, but still within the manual control domain, Cohen and Ferrell [1967] found that subjects' abilities to estimate "readiness" of the driver to perform difficult maneuvers with an automobile were no different if they were to perform the maneuver themselves or they were simply observing another driver (i.e., manual involvement did not enhance performance).

The above studies on prediction, predictor displays, and manual control mainly serve to emphasize the importance of cue utilization in development and use of mental models. Succinctly,

one's conceptualization of how something works is highly influenced by what observations one chooses to make. Therefore, when attempting to identify the cause of suboptimal performance by humans, one should try to avoid confounding information processing limits (e.g., memory) and inappropriate or inadequate cue utilization. In some situations, these two types of limitation seem to have demonstrably different effects [Baron and Berliner, 1977]. However, in general it appears that insufficient attention has been devoted to this issue.

An interesting aspect of cue utilization is the extent to which it differs for novices and experts. In general, experts are not found to be unduly influenced by superficial cues [Chi and Glaser, 1984]. For example, in a study of the use of research literature, Morehead and Rouse [1985] found that faculty members were much more definitive than Ph.D. students in specifying attributes of information that they did <u>not</u> want retrieved. However, there are situations where novices perform relatively better because they utilize more concrete, detailed representations [Adelson, 1984]. Nevertheless, available evidence indicates that an important attribute of expertise is the ability to select the most useful features of problems.

A Central Issue

To the extent that it is reasonable to characterize any

single issue as the central issue, that issue has to be instruction or training. For any particular task, job, or profession, what mental models should humans have and how should these models be imparted? This question is of sufficient theoretical and practical importance to warrant a much more detailed treatment than accorded to the other salient issues considered in this section.

INSTRUCTIONAL ISSUES

The purpose of instruction is to provide the learner with necessary knowledge and skills, as well as improve confidence, attitude, etc. For instruction related to any given system, a subset of the necessary knowledge and skills relates to the ability to describe purpose and form, explain functions and observed states, and predict future states. Therefore, one of the purposes of instruction is to provide necessary mental models.

While this may seem, at least initially, straightforward, it is a very difficult issue. The basic questions are: For a given system, what do the humans involved with that system need to be able to do, and what knowledge is necessary for them to develop and maintain this repertoire of skills? An important related question is: What is the most appropriate form for this knowledge?

Within this section, these questions are considered in terms of the types of knowledge included within the proposed definition of mental models. For the most part, this discussion emphasizes the impacts of particular types of knowledge rather than the more global concepts of mental models. This level of specificity serves to emphasize the potential utility of many of the results cited.*

Knowledge of Theories and Principles

When considering the questions noted above, a fairly common assertion is that humans (particularly operators and maintainers) need to understand thoroughly the fundamental principles upon which the design and operation of the system of interest is based. The "principles" of concern usually include fundamentals of thermodynamics, heat transfer, fluid mechanics, solid mechanics, dynamics, electricity, and perhaps mathematics. Many technical training programs place heavy emphasis on these types of principle.

Unfortunately, there is little if any evidence that this emphasis results in better and more useful mental models. In the

* The need for this level of specificity also serves to highlight the fact that expressing results solely in terms of global and somewhat vague concepts tends to dissipate any impact these results might potentially have.

domain of process control, a variety of independent studies have shown that explicit training in knowledge of theories, fundamentals, or principles did not enhance performance, and sometimes actually degraded performance [Crossman and Cooke, 1962; Kragt and Landeweerd, 1974; Brigham and Laios, 1975; Shepherd, et al., 1977; Morris and Rouse, 1985]. It has also been found that scores on tests of fundamental understanding did not correlate significantly with process control performance [Surgenor and McGeachy, 1983; Morris and Rouse, 1985].

Similar results have been found in the domain of electronics troubleshooting. Schorgmayer and Swanson [1975] determined that an account of system functioning did not enhance performance relative to procedural assistance. Williams and Whitmore [1959] found that knowledge of theory was greatest and troubleshooting performance poorest immediately following training; the opposite conclusions were reached when the same subjects were tested three years later. Foley [1977] reviewed seven studies of troubleshooting, including that of Williams and Whitmore, and concluded that performance on tests of theory and job knowledge did not correlate with actual job performance.

Results in the domain of mathematical problem solving are also similar. Two studies compared training that emphasized general understanding of mathematical principles to training that stressed calculational techniques [Mayer and Greeno, 1972;

Mayer, et al., 1977]. For both studies, it was found that general understanding was better for answering questions about mathematics, while knowledge of calculational techniques was better for actually solving problems.

A very consistent picture emerges from the above studies of process control, electronics troubleshooting, and mathematical problem solving. While the theories, fundamentals, and principles were certainly relevant to the systems and tasks investigated, this knowledge did not have observable effects on the performance of the operators, maintainers, and problem solvers studied. It seems reasonable to assert that theoretically-oriented training increased knowledge about the system and task, but the form and/or guidance in use of this knowledge were not sufficient to improve performance and, in some instances, were such that performance was degraded.

Related to this issue is the research of Eylon and Reif [1984] who studied the effects of forms of knowledge organization on college-level physics problem solving. They found that hierarchical organizations had positive effects, particularly for the better students. They conclude that the organization of knowledge for instruction is as important as the content of instruction.

Guidance and Cueing

Guidance in the use of knowledge can occur in several ways. Many of the studies noted above provided trainees with explicit procedures for performing their tasks. In some cases, the comparison was procedures vs. principles; in other cases, training via procedures served as more of a control group. In general, procedures tended to be at least as useful as principles, and at least as useful as having both procedures and principles.

Procedures represent an extreme form of converting general principles into operationally-useful guidance. A less extreme form of guidance involves simply informing trainees of how and when the knowledge gained during training should be used, without telling them exactly what they should do. A variety of studies in problem solving [Reed, et al., 1974; Weisberg, et al., 1978], word puzzles [Perfetto, et al., 1983], and mathematics [Mayer, et al., 1977] have considered the effect of this type of "cueing" and found it to be necessary if clues, analogies, and general principles are to be transferred successfully to task performance subsequent to training.

It is not always possible for guidance to be explicit. If systems are very complex and/or completely unanticipated situations may arise, it is likely to be impossible to synthesize

procedures that can be validated in the sense of assuring success. Similarly, it may be impossible to inform trainees of how and when knowledge will be applicable (i.e., "cueing" may not be viable). Nevertheless, one hopes that the knowledge gained during training will be called upon when unusual situations arise.

One approach to enhancing this possibility is to provide training in a variety of contexts (e.g., for more than one system, one or more of which may be unfamiliar). The use of unfamiliar contexts can "force" trainees to utilize general principles such as analogies because that may be the only way in which they can succeed. Rouse and Hunt [1984] have investigated various aspects of this concept as applied to troubleshooting training. While they found that the use of unfamiliar contexts is somewhat more subtle and complicated than originally anticipated, the concept was sufficiently viable and useful to become an important element in training programs in the aviation and marine domains [Rouse, 1982-83]. Brooke and his colleagues [1980] have also investigated a variation of this concept and found that training in multiple contexts improved transfer of problem solving skills to new contexts.

These results serve to emphasize the possibility that human performance within a particular system context may be significantly affected by their knowledge of other contexts.

Thus, not only are tasks within a particular system likely to be addressed via multiple mental models of that system, but task performance may also be influenced by mental models of other systems and classes of systems. This leads to the issue of prior knowledge.

Effects of Prior Knowledge

With the possible exception of very young children, instruction never involves the filling of a tabula rasa. Trainees always approach an instructional experience with prior knowledge and skills. In particular, trainees always have a variety of a priori mental models which provide both opportunities and difficulties from an instructional point of view.

The availability of prior knowledge presents an opportunity in that it can serve as a basis for gaining new knowledge. In fact, it can be argued that prior knowledge will almost certainly affect learning [Glaser, 1984]. For example, in the domain of human-computer interaction, Carroll and Thomas [1982] argue that new "cognitive structures" are developed by using metaphors to existing cognitive structures. Norman and his colleagues [1976] offer a similar assertion with regard to the design of instructional programs. Rasmussen [1979, 1983] discusses implications of alternative mental models for display design and

suggests that analogies offer an important mechanism for matching displays to humans' models. With regard to analogies, Gentner and Gentner [1983] found that the usefulness of analogies in solving electricity problems was greatest when people used their own a priori analogies rather than using those that they had only recently learned as part of the instructions associated with the equipment.

While existing "cognitive structures" offer a foundation on which to build, they also can be an impediment. Prior knowledge that is incorrect will not necessarily be discarded once the correct knowledge is provided. Instead, an amalgam of the correct and incorrect may be retained, especially if the incorrect aspects are such that everyday life experiences are unlikely to yield any inconsistencies.

This phenomenon has emerged several times in studies of physics problem solving. As discussed earlier, DiSessa [1982] and McCloskey [1983] both found that students' naive, "pre-Newtonian" views of motion persisted even after college-level instruction had provided them with more appropriate formulations. Similarly, Clement [1983] found that the "motion implies force" misconception was retained after college-level instruction had provided the appropriate conceptualization. The implication of these findings is that instruction must remediate a priori misconceptions as well as provide correct knowledge.

Summary

Summarizing the evidence presented in this section on instructional issues, the following assertions seem reasonable*:

1. Knowledge of theories, fundamentals, and principles does not necessarily enhance task performance; measures of the extent of such knowledge are not good predictors of task performance.

2. The operational utility of this type of knowledge is highly dependent on the form in which it is presented and the guidance in its use that is provided.

3. Guidance in the use of knowledge can be explicit in terms of procedures and cueing, or implicit by providing a range of training experiences that foster or require the use of knowledge.

4. A priori knowledge can serve as a powerful basis for gaining new knowledge or, if incorrect, an impediment to gaining correct knowledge; both cases argue for consideration of a priori knowledge in designing instructional programs.

From the perspective of mental models, the above assertions imply that the form of knowledge, guidance in use of knowledge, and prior knowledge all interact to affect the development and use of mental models.

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*Morris and Rouse (1985), in a recent comprehensive review of empirical research on human performance in troubleshooting tasks, present considerable evidence for a similar set of assertions relative to training for troubleshooting tasks.

FUNDAMENTAL LIMITS

At many points throughout the discussions in this paper various considerations have arisen that appear to pose limits to understanding the "true" nature of mental models, particularly for any specific individual and situation. In this section, the apparent characteristics of these limits are formalized and explored. The purpose of this discussion is to outline clearly what appear to be fundamental limits in the search for mental models.

One of these limits is fundamental to science in general. Scientists' conceptualizations of phenomena are almost totally dependent on their own mental models. These models dictate what observations are made and how the resulting data is organized. The ultimate subjectivity and arbitrariness of this process has long been recognized [James, 1909; Whitehead, 1925]. However, only recently has it come to be viewed as a predominant aspect of the social and psychological processes within science [Kuhn, 1962; Zukav, 1979].

This subjectivity and arbitrariness is particularly problematic in the behavioral sciences. As Ziman [1968] has emphasized, controversy and uncertainty seem to be endemic in psychology, where many of the basic phenomena are familiar to both researchers and laymen. These problems are aggravated in

the study of mental models because, in effect, such studies amount to one or more humans developing models of other humans' models of the external world. This dilemma is fundamental in that it cannot be resolved. However, the effects of this problem can perhaps be lessened if researchers are aware of the biases that they bring to a study, and that these biases may not be indicative of the tendencies of the population of subjects being studied. Therefore, for example, it is important for scientists and engineers to avoid the presumption that operators, maintainers, and managers approach their systems from a scientific or engineering perspective.

Beyond the limits imposed by investigators' biases, there are difficulties that preclude uncovering the "truth." Several of these difficulties are discussed, or at least alluded to, in earlier sections of this paper. The discussion of identification methods considered several important limitations. It was noted that empirical approaches are limited by the fact that behavioral effects of access and manipulation of mental models may possibly be confounded with perception and response execution. Analytical approaches that consider the possibility of other than perfect mental models must choose among an infinity of alternative imperfect models.

In an attempt to generalize across domains, it was suggested that the specificity and perhaps the form of conceptualizations

of mental models are limited by the location of a domain along two dimensions: 1) nature of model manipulation, ranging from implicit to explicit, and 2) level of behavioral discretion, ranging from none to full. This two-dimensional characterization of differences among domains appears to have clear implications for the potential usefulness of alternative identification methods. Namely, inferential methods seem to work best when there is little behavioral discretion, while verbalization methods appear to be most successful when explicit model manipulation is inherent to the task of interest.

If the above limitations are, in fact, fundamental, then the search for mental models will never comletely eliminate uncertainty; the black box will never be completely transparent. This type of problem has been addressed by particle physicists, who ultimately accepted this inherent limitation in terms of Heisenberg's uncertainty principle [Heisenberg, 1958; Zukav, 1979]. The basic idea is that one cannot measure perfectly both the position and momentum (the product of mass and velocity) of a particle, because the process of measuring position produces uncertainty in momentum and vice versa. Heisenberg [1958] generalizes this notion by stating, "What we observe is not nature itself but nature exposed to our method of questioning."

The general perspective provided by this statement, as well as the specifics of the uncertainty principle, appear to be quite

relevant to research on mental models. Much of the literature implies that mental models are static, unitary entities that can be identified if appropriate methods are employed. However, as Norman [1983] notes, this view is much too simplistic. Available evidence suggests that mental models are more likely to be dynamic entities that can have a multiplicity of forms.

If, at least for the sake of argument, one asserts that mental models are analogous to physicists' elementary particles which are dynamic entities that can be in multiple states, then it is quite straightforward to map the physicists' uncertainty principle to an analagous principle for mental models. The position of a particle is analogous to the current state of a mental model (i.e., what it is now) and the velocity (or momentum) of a particle is analagous to the changes occurring in a mental model (i.e., what it is becoming).

Uncertainty is fundamental in the following ways. In order to measure perfectly what a mental model is now, one inevitably intrudes on what the model is becoming. Less intrusive measurement methods reduce the effects on future model states, but increase the uncertainty about the current state. Similarly, if one attempts to measure perfectly what a model is becoming, in attempting to measure these changes, one introduces uncertainty about the instantaneous state of the model (i.e., what it is now) relative to which these changes are being measured.

Heisenberg's principle specifies that the product of the uncertainties in position and momentum is constant (i.e., Heisenberg's constant!). The psychological analog of this constant is not apparent. In fact, it seems reasonable to conjecture that the magnitude of this constant might be domain dependent in the sense that the dimensions in Figure 2 may affect the level of inherent uncertainty. Despite the intuitive appeal of such a formulation, it must be remembered, however, that it is totally a conjecture.

This raises the question of how this line of reasoning might move beyond pure conjecture. Certainly, more thought is needed and a mathematical/logical formulation might be possible. While progress might be made in this way, it is also possible that a limit such as that of Godel may be reached, where "truth" cannot be proven and must simply be accepted [Godel, 1962; Guillen, 1983]. Obviously, the possibility of such "meta" limits is yet another conjecture at this point in time.

This section has outlined several fundamental limits in the search for mental models, as well as several conjectures regarding limits to "knowing what can be known." The intent of this discussion was to illustrate why pursuit of "truth" may be inherently elusive, particularly when studying mental models. Given these limits, dogged pursuit of "truth" is unreasonable. Instead, the emphasis should be on the utility of research on

mental models for system design, instruction, etc. This pragmatic view of science is hardly new [Peirce, 1878; James, 1907]; however, it often seems to be forgotten.

CONCLUSIONS

This paper has explored a wide range of issues associated with research on mental models. At this point in time, this area of study is rife with terminological inconsistencies and a preponderance of conjectures rather than data. This situation is, to a great extent, due to the fact that a variety of subdisciplines have adopted the concept of mental models and proceeded to develop their own terminology and methodology, independent of past or current work in this area in other subdisciplines.

Nowhere is this situation more evident than in the important matter of definitions. In many cases, the phrase "mental models" appears to be simply a substitute for "knowledge" in general. Such a substitution is not particularly useful. This paper has suggested a more concise working definition, based on a functional perspective: mental models are the mechanisms whereby humans generate descriptions of system purpose and form, explanations of system functioning and observed systems states, and predictions of future system states. Much of the discussion in this paper is premised on this definition.

A portion of this discussion has focused on limits in identifying or capturing mental models. Some of the difficulties in this area are due to the likelihood that mental models are dynamic entities that can have a multiplicity of forms, even for a particular individual in a specific situation. Beyond this issue, other types of limit may be more fundamental. The biases imposed by scientists' own mental models and the possibility of an uncertainty principle have been suggested as fundamental in nature. All of the limits outlined in this paper have practical implications. For example, the design of "expert systems" is premised on humans' abilities to verbalize their models; in light of the above discussion, this ability would appear to be more limited than is commonly assumed.

Despite the fundamental nature of some of the limits outlined in this paper, the issues underlying the mental models construct are important and deserve substantial attention. What is needed, however, is to move away from the perception that "truth" is being sought and, instead, emphasize the utility of researching these issues to advance the state of understanding of learning, problem solving, etc. This shift should help to eliminate many minor issues, most of which appear to emanate from a rather zealous tendancy to coin new terminology.

By purging the debate of these minor issues, research should be able to focus on the major, substantive issues including

accessibility, form and content of representation, nature of expertise, cue utilization, and, of most importance, instructional issues. The literature is replete with insightful thinking on these issues and a variety of interesting and potentially important hypotheses have been suggested. Unfortunately, however, there is a paucity of solid emirical data available to support or refute these hypctheses. At the moment, the research community's ability to generate conjectures and publish them seems to be much greater than its ability to test them empirically. What is needed are innovative (and validated) empirical approaches to employing the mental models construct usefully, most likely involving a mix of several traditional experimental methods with newer methods such as computational modeling and linguistic analysis.

To conclude, the search for mental models is potentially of great importance: any success that is achieved is likely to have substantial impacts on system design, training, etc. However, there are fundamental limits on what can be clearly seen on looking into the black box. It appears that these limits will have to be accepted as precluding the uncovering of "truth." Fortunately, truth may not be necessary. If a pragmatic perspective is adopted, research on mental models can avoid the ephemeral issues and concentrate on providing rigorously tested answers to a variety of far-reaching and important questions.

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Personnel Analysis Division
AF/MPXA
5C360, The Pentagon
Washington, DC 20330

Air Force Human Resources Lab
AFHRL/MPD
Brooks AFB, TX 78235

Air Force Office
of Scientific Research
Life Sciences Directorate
Bolling Air Force Base
Washington, DC 20332

Dr. Robert Ahlers
Code N711
Human Factors Laboratory
NAVTRAEQUIPCEN
Orlando, FL 32813

Dr. Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152

Dr. William E. Alley
AFHRL/MOT
Brooks AFB, TX 78235

Dr. Earl A. Alluisi
HQ, AFHRL (AFSC)
Brooks AFB, TX 78235

Dr. John R. Anderson
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. Phipps Arabie
University of Illinois
Department of Psychology
603 E. Daniel St.
Champaign, IL 61820

Technical Director
Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Special Assistant for Projects
OASN(M&RA)
5D800, The Pentagon
Washington, DC 20350

Dr. Alan Baddeley
Medical Research Council
Applied Psychology Unit
15 Chaucer Road
Cambridge CB2 2EF
ENGLAND

Dr. Patricia Baggett
University of Colorado
Department of Psychology
Box 345
Boulder, CO 80309

Dr. Eva L. Baker, Director
UCLA Center for the Study
of Evaluation
145 Moore Hall
University of California
Los Angeles, CA 90024

Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08450

Dr. John Black
Yale University
Box 11A, Yale Station
New Haven, CT 06520

Code N711
Attn: Arthur S. Blaiwes
Naval Training Equipment Center
Orlando, FL 32813

Dr. R. Darrell Bock
University of Chicago
Department of Education
Chicago, IL 60637

Dr. Jeff Bonar
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Nick Bond
Office of Naval Research
Liaison Office, Far East
APO San Francisco, CA 96503

Dr. Lyle Bourne
Department of Psychology
University of Colorado
Boulder, CO 80309

Dr. Gordon H. Bower
Department of Psychology
Stanford University
Stanford, CA 94306

Dr. Richard Braby
NTEC Code 10
Orlando, FL 32751

Dr. Robert Breaux
Code N-095R
NAVTRAEQUIPCEN
Orlando, FL 32813

Dr. Ann Brown
Center for the Study of Reading
University of Illinois
51 Gerty Drive
Champaign, IL 61280

Dr. John S. Brown
XEROX Palo Alto Research
Center
3333 Coyote Road
Palo Alto, CA 94304

Dr. Bruce Buchanan
Computer Science Department
Stanford University
Stanford, CA 94305

Dr. Patricia A. Butler
NIE Mail Stop 1806
1200 19th St., NW
Washington, DC 20208

Dr. Jaime Carbonell
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

Mr. James W. Carey
Commandant (G-PTE)
U.S. Coast Guard
2100 Second Street, S.W.
Washington, DC 20593

Dr. Susan Carey
Harvard Graduate School of
Education
337 Gutman Library
Appian Way
Cambridge, MA02138

Dr. Pat Carpenter
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

Dr. Robert Carroll
NAVOP 01B7
Washington, DC 20370

Dr. Fred Chang
Navy Personnel R&D Center
Code 51
San Diego, CA 92152

Dr. Davida Charney
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Eugene Charniak
Brown University
Computer Science Department
Providence, RI 02912

Dr. Michelene Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Dr. Susan Chipman
Code 442PT
Office of Naval Research
800 N. Quincy St.
Arlington, VA 22217-5000

Dr. Yee-Yeen Chu
Perceptronics, Inc.
21111 Erwin Street
Woodland Hills, CA 91367-3713

Dr. William Clancey
Computer Science Department
Stanford University
Stanford, CA 94306

Director
Manpower Support and
Readiness Program
Center for Naval Analysis
2000 North Beauregard Street
Alexandria, VA 22311

Scientific Advisor
to the DCNO (MPT)
Center for Naval Analysis
2000 North Beauregard Street
Alexandria, VA 22311

Chief of Naval Education
and Training
Liaison Office
Air Force Human Resource Laboratory
Operations Training Division
Williams AFB, AZ 85224

Assistant Chief of Staff
Research, Development,
Test, and Evaluation
Naval Education and
Training Command (N-5)
NAS Pensacola, FL 32508

Dr. Michael Cole
University of California
at San Diego
Laboratory of Comparative
Human Cognition - D003A
La Jolla, CA 92093

Dr. Allan M. Collins
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Stanley Collyer
Office of Naval Technology
800 N. Quincy Street
Arlington, VA 22217

Dr. Leon Cooper
Brown University
Center for Neural Science
Providence, RI 02912

Dr. Lynn A. Cooper
Learning R&D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Dr. Lee Cronbach
16 Laburnum Road
Atherton, CA 94205

Dr. Mary Cross
Department of Education
Adult Literacy Initiative
Room 4145
400 Maryland Avenue, SW
Washington, DC 20202

CTB/McGraw-Hill Library
2500 Garden Road
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CDR Mike Curran
Office of Naval Research
800 N. Quincy St.
Code 270
Arlington, VA 22217-5000

Bryan Dallman
AFHRL/LRT
Lowry AFB, CO 80230

Dr. Charles E. Davis
Personnel and Training Research
Office of Naval Research
Code 442PT
800 North Quincy Street
Arlington, VA 22217-5000

Defense Technical
Information Center
Cameron Station, Bldg 5
Alexandria, VA 22314
Attn: TC
(12 Copies)

Dr. Thomas M. Duffy
Communications Design Center
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Edward E. Eddowes
CNATRA N301
Naval Air Station
Corpus Christi, TX 78419

Dr. John Ellis
Navy Personnel R&D Center
San Diego, CA 92252

Dr. Jeffrey Elman
University of California,
San Diego
Department of Linguistics, C-008
La Jolla, CA 92093

Dr. Richard Elster
Deputy Assistant Secretary
of the Navy (Manpower)
Washington, DC 20350

Dr. Susan Embretson
University of Kansas
Psychology Department
Lawrence, KS 66045

ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, MD 20014

Dr. K. Anders Ericsson
University of Colorado
Department of Psychology
Boulder, CO 80309

Edward Esty
Department of Education, OERI
MS 40
1200 19th St., NW
Washington, DC 20208

Dr. Beatrice J. Farr
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Marshall J. Farr
2520 North Vernon Street
Arlington, VA 22207

Dr. Pat Federico
Code 511
NPRDC
San Diego, CA 92152

Mr. Wallace Feurzeig
Educational Technology
Bolt Beranek & Newman
10 Moulton St.
Cambridge, MA 02238

Dr. Craig I. Fields
ARPA
1400 Wilson Blvd.
Arlington, VA 22209

Dr. Gerhard Fischer
Liebiggasse 5/3
A 1010 Vienna
AUSTRIA

Dr. Linda Flower
Carnegie-Mellon University
Department of English
Pittsburgh, PA 15213

Dr. Ken Forbus
Department of Computer Science
University of Illinois
Champaign, IL 61820

Dr. Carl H. Frederiksen
McGill University
3700 McTavish Street
Montreal, Quebec H3A 1Y2
CANADA

Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

Dr. Norman Frederiksen
Educational Testing Service
Princeton, NJ 08541

Dr. Michael Genesereth
Stanford University
Computer Science Department
Stanford, CA 94305

Dr. Dedre Gentner
University of Illinois
Department of Psychology
603 S. Daniel St.
Champaign, IL 61820

Dr. Don Gentner
Center for Human
Information Processing
University of California
La Jolla, CA 92093

Dr. Robert Glaser
Learning Research
& Development Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Dr. Arthur M. Glenberg
University of Wisconsin
W. J. Brogden Psychology Bldg.
1202 W. Johnson Street
Madison, WI 53706

Dr. Marvin D. Glock
13 Stone Hall
Cornell University
Ithaca, NY 14853

Dr. Joseph Goguen
Computer Science Laboratory
SRI International
333 Ravenswood Avenue
Menlo Park, CA 94025

Dr. Daniel Gopher
Industrial Engineering
& Management
TECHNION
Haifa 32000
ISRAEL

Dr. Sherrie Gott
AFHRL/MODJ
Brooks AFB, TX 78235

Dr. Richard H. Granger
Department of Computer Science
University of California, Irvine
Irvine, CA 92717

Dr. Bert Green
Johns Hopkins University
Department of Psychology
Charles & 34th Street
Baltimore, MD 21218

Dr. James G. Greeno
University of California
Berkeley, CA 94720

Dr. Henry M. Halff
Halff Resources, Inc.
4918 33rd Road, North
Arlington, VA 22207

Dr. Ronald K. Hambleton
Laboratory of Psychometric and
Evaluative Research
University of Massachusetts
Amherst, MA 01003

Mr. William Hartung
PEAM Product Manager
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Wayne Harvey
SRI International
333 Ravenswood Ave.
Room B-S324
Menlo Park, CA 94025

Prof. John R. Hayes
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Barbara Hayes-Roth
Department of Computer Science
Stanford University
Stanford, CA 95305

Dr. Frederick Hayes-Roth
Teknowledge
525 University Ave.
Palo Alto, CA 94301

Dr. Joan I. Heller
Graduate Group in Science and
Mathematics Education
c/o School of Education
University of California
Berkeley, CA 94720

Dr. Jim Hollan
Code 51
Navy Personnel R & D Center
San Diego, CA 92152

Dr. John Holland
University of Michigan
2313 East Engineering
Ann Arbor, MI 48109

Dr. Melissa Holland
Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Keith Holyoak
University of Michigan
Human Performance Center
330 Packard Road
Ann Arbor, MI 48109

Dr. Lloyd Humphreys
University of Illinois
Department of Psychology
603 East Daniel Street
Champaign, IL 61820

Dr. Earl Hunt
Department of Psychology
University of Washington
Seattle, WA 98105

Dr. Ed Hutchins
Navy Personnel R&D Center
San Diego, CA 92152

Dr. Dillon Inouye
WICAT Education Institute
Provo, UT 84057

Dr. Zachary Jacobson
Bureau of Management Consulting
365 Laurier Avenue West
Ottawa, Ontario K1A 0S5
CANADA

Dr. Joseph E. Johnson
Assistant Dean for
Graduate Studies
College of Science and Mathematics
University of South Carolina
Columbia, SC 29208

Dr. Douglas H. Jones
Advanced Statistical
Technologies Corporation
10 Trafalgar Court
Lawrenceville, NJ 08148

Dr. Marcel Just
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Milton S. Katz
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Steven W. Keele
Department of Psychology
University of Oregon
Eugene, OR 97403

Maj. John Keene
ADP Systems Branch
C3 Development Center (D104)
MCDEC
Quantico, VA 22134

Dr. Scott Kelso
Haskins Laboratories,
270 Crown Street
New Haven, CT 06510

Dr. Norman J. Kerr
Chief of Naval Education
and Training
Code 00A2
Naval Air Station
Pensacola, FL 32508

Dr. Dennis Kibler
University of California
Department of Information
and Computer Science
Irvine, CA 92717

Dr. David Kieras
University of Michigan
Technical Communication
College of Engineering
1223 E. Engineering Building
Ann Arbor, MI 48109

Rouse & Morris, "Limits in the Search for Mental Models"

Dr. Peter Kincaid
Training Analysis
& Evaluation Group
Department of the Navy
Orlando, FL 32813

Dr. Walter Kintsch
Department of Psychology
University of Colorado
Campus Box 345
Boulder, CO 80302

Dr. David Klahr
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Mazie Knerr
Program Manager
Training Research Division
HumRRO
1100 S. Washington
Alexandria, VA 22314

Dr. Janet L. Kolodner
Georgia Institute of Technology
School of Information
& Computer Science
Atlanta, GA 30332

Dr. Stephen Kosslyn
Harvard University
1236 William James Hall
33 Kirkland St.
Cambridge, MA 02138

Dr. Kenneth Kotovsky
Department of Psychology
Community College of
Allegheny County
800 Allegheny Avenue
Pittsburgh, PA 15233

Dr. Benjamin Kuipers
MIT Laboratory for Computer Science
545 Technology Square
Cambridge, MA 02139

Dr. Patrick Kyllonen
AFHRL/MOE
Brooks AFB, TX 78235

Dr. Pat Langley
University of California
Department of Information
and Computer Science
Irvine, CA 92717

Dr. Marcy Lansman
University of North Carolina
The L. L. Thurstone Lab.
Davie Hall 013A
Chapel Hill, NC 27[illegible]4

Dr. Kathleen [illegible]
Naval Health [illegible]
Education [illegible] Command
Naval Medical Command,
National Capital Region
Bethesda, MD 2[illegible]14-5022

Dr. Jill Larkin
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 1521[illegible]

Dr. Alan M. Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Jim Levin
University of California
Laboratory for Comparative
Human Cognition
D003A
La Jolla, CA 92093

Dr. Michael Levine
Educational Psychology
210 Education Bldg.
University of Illinois
Champaign, IL 61801

Dr. Clayton Lewis
University of Colorado
Department of Computer Science
Campus Box 430
Boulder, CO 80309

Science and Technology Division
Library of Congress
Washington, DC 20540

Dr. Charlotte Linde
SRI International
333 Ravenswood Avenue
Menlo Park, CA 94025

Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

Dr. Frederic M. Lord
Educational Testing Service
Princeton, NJ 08541

Dr. Don Lyon
P. O. Box 44
Higley, AZ 85236

Dr. William L. Maloy (02)
Chief of Naval Education
and Training
Naval Air Station
Pensacola, FL 32508

Dr. Sandra P. Marshall
Department of Psychology
University of California
Santa Barbara, CA 93106

Dr. Richard E. Mayer
Department of Psychology
University of California
Santa Barbara, CA 93106

Dr. Jay McClelland
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. James L. McGaugh
Center for the Neurobiology
of Learning and Memory
University of California, Irvine
Irvine, CA 92717

Dr. Kathleen McKeown
Columbia University
Department of Computer Science
New York, NY 10027

Dr. Joe McLachlan
Navy Personnel R&D Center
San Diego, CA 92152

Dr. James McMichael
Navy Personnel R&D Center
San Diego, CA 92152

Dr. Barbara Means
Human Resources
Research Organization
1100 South Washington
Alexandria, VA 22314

Dr. Arthur Melmed
U. S. Department of Education
724 Brown
Washington, DC 20208

Dr. Al Meyrowitz
Office of Naval Research
Code 433
800 N. Quincy
Arlington, VA 22217-5000

Dr. George A. Miller
Department of Psychology
Green Hall
Princeton University
Princeton, NJ 08540

Dr. Robert Mislevy
Educational Testing Service
Princeton, NJ 08541

Dr. Andrew R. Molnar
Scientific and Engineering
Personnel and Education
National Science Foundation
Washington, DC 20550

Dr William Montague
NPRDC Code 13
San Diego, CA 92152

Headquarters, Marine Corps
Code MPI-20
Washington, DC 20380

Dr. Allen Munro
Behavioral Technology
Laboratories - USC
1845 S. Elena Ave., 4th Floor
Redondo Beach, CA 90277

Director
Distribution Department
Naval Military Personnel Command
N-4
Washington, DC 20370

Head, HRM Operations Branch
Naval Military Personnel Command
N-62F
Washington, DC 20370

Assistant for Evaluation,
Analysis, and MIS
Naval Military Personnel Command
N-6C
Washington, DC 20370

Spec. Asst. for Research, Experimental & Academic Programs
Naval Technical Training Command
(Code 016)
NAS Memphis (75)
Millington, TN 38054

Program Manager for Manpower,
Personnel, and Training
NAVMAT 0722
Arlington, VA 22217-5000

Dr. David Navon
Institute for Cognitive Science
University of California
La Jolla, CA 92093

Assistant for Planning MANTRAPERS
NAVOP 01B6
Washington, DC 20370

Head
Workforce Information Section
NAVOP 140F
Washington, DC 20370

Head
Manpower, Personnel, Training
and Reserve Team
NAVOP 914D
5A578, The Pentagon
Washington, DC 20350

Leadership Management Education
and Training Project Officer
Naval Medical Command (Code 05C)
Washington, DC 20372

Mr. Bill Neale
HQ ATC/TTA
Randolph AFB, TX 78148

Technical Director
Navy Health Research Center
P.O. Box 85122
San Diego, CA 92138

Dr. Richard E. Nisbett
University of Michigan
Institute for Social Research
Room 5261
Ann Arbor, MI 48109

Dr. Donald A. Norman
Institute for Cognitive Science
University of California
La Jolla, CA 92093

Dr. Melvin R. Novick
356 Lindquist Center
for Measurement
University of Iowa
Iowa City, IA 52242

Director, Training Laboratory
NPRDC (Code 05)
San Diego, CA 92152

Director, Manpower and Personnel
Laboratory
NPRDC (Code 06)
San Diego, CA 92152

Director
Human Factors
& Organizational Systems Lab.
NPRDC (Code 07)
San Diego, CA 92152

Fleet Support Office
NPRDC (Code 301)
San Diego, CA 92152

Library
Code P201L
Navy Personnel R&D Center
San Diego, CA 92152

Technical Director
Navy Personnel R&D Center
San Diego, CA 92152

Commanding Officer
Naval Research Laboratory
Code 2627
Washington, DC 20390

Dr. Harry F. O'Neil, Jr.
Training Research Lab
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Stellan Ohlsson
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Director Technology Programs
Office of Naval Research
Code 200
800 North Quincy Street
Arlington, VA 22217-5000

Director Research Programs
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217-5000

Mathematics Group
Office of Naval Research
Code 411MA
800 North Quincy Street
Arlington, VA 22217-5000

Office of Naval Research
Code 433
800 N. Quincy Street
Arlington, VA 22217-5000

Office of Naval Research
Code 442
800 N. Quincy St.
Arlington, VA 22217-5000

Office of Naval Research
Code 442EP
800 N. Quincy Street
Arlington, VA 22217-5000

Group Psychology Program
Code 442GP
Office of Naval Research
800 N. Quincy St.
Arlington, VA 22217-5000

Office of Naval Research
Code 442PT
800 N. Quincy Street
Arlington, VA 22217-5000
(6 Copies)

Special Assistant for Marine
Corps Matters
Code 100M
Office of Naval Research
800 N. Quincy St.
Arlington, VA 22217-5000

Psychologist
ONR Branch Office
1030 East Green Street
Pasadena, CA 91101

Commanding Officer
Army Research Institute
ATTN: PERI-BR (Dr. J. Orasanu)
5001 Eisenhower Avenue
Alexandria, VA 22333

Prof. Seymour Papert
20C-109
Massachusetts Institute
of Technology
Cambridge, MA 02139

Dr. James Paulson
Department of Psychology
Portland State University
P.O. Box 751
Portland, OR 97207

Dr. Douglas Pearse
DCIEM
Box 2000
Downsview, Ontario
CANADA

Dr. James W. Pellegrino
University of California,
Santa Barbara
Department of Psychology
Santa Barbara, CA 93106

Dr. Nancy Pennington
University of Chicago
Graduate School of Business
1101 E. 58th St.
Chicago, IL 60637

Military Assistant for Training and
Personnel Technology
OUSD (R & E)
Room 3D129, The Pentagon
Washington, DC 20301

LCDR Frank C. Petho, MSC, USN
CNATRA Code N36, Bldg. 1
NAS
Corpus Christi, TX 78419

Dr. Tjeerd Plomp
Twente University of Technology
Department of Education
P.O. Box 217
7500 AE ENSCHEDE
THE NETHERLANDS

Dr. Martha Polson
Department of Psychology
Campus Box 346
University of Colorado
Boulder, CO 80309

Dr. Peter Polson
University of Colorado
Department of Psychology
Boulder, CO 80309

Dr. Steven E. Poltrock
MCC
9430 Research Blvd.
Echelon Bldg #1
Austin, TX 78759-6509

Dr. Harry E. Pople
University of Pittsburgh
Decision Systems Laboratory
1360 Scaife Hall
Pittsburgh, PA 15261

Dr. Mike Posner
University of Oregon
Department of Psychology
Eugene, OR 97403

Dr. Joseph Psotka
ATTN: PERI-1C
Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

Dr. Mark D. Reckase
ACT
P. O. Box 168
Iowa City, IA 52243

Dr. Lynne Reder
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. James A. Reggia
University of Maryland
School of Medicine
Department of Neurology
22 South Greene Street
Baltimore, MD 21201

Dr. Fred Reif
Physics Department
University of California
Berkeley, CA 94720

Dr. Lauren Resnick
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Dr. Gil Ricard
Code N711
NAVTRAEQUIPCEN
Orlando, FL 32813

Dr. Mary S. Riley
Program in Cognitive Science
Center for Human Information
Processing
University of California
La Jolla, CA 92093

William Rizzo
Code 712 NAVTRAEQUIPCEN
Orlando, FL 32813

Dr. Andrew M. Rose
American Institutes
for Research
1055 Thomas Jefferson St., NW
Washington, DC 20007

Dr. Ernst Z. Rothkopf
AT&T Bell Laboratories
Room 2D-456
600 Mountain Avenue
Murray Hill, NJ 07974

Dr. William B. Rouse
Georgia Institute of Technology
School of Industrial & Systems
Engineering
Atlanta, GA 30332

Dr. Donald Rubin
Statistics Department
Science Center, Room 608
1 Oxford Street
Harvard University
Cambridge, MA 02138

Dr. David Rumelhart
Center for Human
Information Processing
Univ. of California
La Jolla, CA 92093

Dr. E. L. Saltzman
Haskins Laboratories
270 Crown Street
New Haven, CT 06510

Dr. Fumiko Samejima
Department of Psychology
University of Tennessee
Knoxville, TN 37916

Dr. Michael J. Samet
Perceptronics, Inc
6271 Variel Avenue
Woodland Hills, CA 91364

Dr. Robert Sasmor
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Roger Schank
Yale University
Computer Science Department
P.O. Box 2158
New Haven, CT 06520

Dr. Walter Schneider
University of Illinois
Psychology Department
603 E. Daniel
Champaign, IL 61820

Dr. Alan H. Schoenfeld
University of California
Department of Education
Berkeley, CA 94720

Dr. Janet Schofield
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Judah L. Schwartz
MIT
20C-120
Cambridge, MA 02139

Dr. Judith Segal
Room 819F
NIE
1200 19th Street N.W.
Washington, DC 20208

DR. ROBERT J. SEIDEL
US Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

Dr. Ramsay W. Selden
NIE
Mail Stop 1241
1200 19th St., NW
Washington, DC 20208

Dr. Michael G. Shafto
ONR Code 442PT
800 N. Quincy Street
Arlington, VA 22217-5000

Dr. Sylvia A. S. Shafto
National Institute of Education
1200 19th Street
Mail Stop 1806
Washington, DC 20208

Dr. Ted Shortliffe
Computer Science Department
Stanford University
Stanford, CA 94305

Dr. Lee Shulman
Stanford University
1040 Cathcart Way
Stanford, CA 94305

Dr. Robert S. Siegler
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Zita M Simutis, Chief
Instructional Technology
Systems Area
ARI
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. H. Wallace Sinaiko
Manpower Research
and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

Dr. Derek Sleeman
Stanford University
School of Education
Stanford, CA 94305

Dr. Edward E. Smith
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Alfred F. Smode
Senior Scientist
Code 7B
Naval Training Equipment Center
Orlando, FL 32813

Dr. Richard Snow
Liaison Scientist
Office of Naval Research
Branch Office, London
Box 39
FPO New York, NY 09510

Dr. Elliot Soloway
Yale University
Computer Science Department
P.O. Box 2158
New Haven, CT 06520

Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152

Dr. Kathryn T. Spoehr
Brown University
Department of Psychology
Providence, RI 02912

James J. Staszewski
Research Associate
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Marian Stearns
SRI International
333 Ravenswood Ave.
Room B-S324
Menlo Park, CA 94025

Dr. Frederick Steinheiser
CIA-ORD
612 Ames
Washington, DC 20505

Dr. Robert Sternberg
Department of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

Dr. Saul Sternberg
University of Pennsylvania
Department of Psychology
3815 Walnut Street
Philadelphia, PA 19104

Dr. Albert Stevens
Bolt Beranek & Newman, Inc.
10 Moulton St.
Cambridge, MA 02238

Dr. Paul J. Sticha
Senior Staff Scientist
Training Research Division
HumRRO
1100 S. Washington
Alexandria, VA 22314

Dr. Thomas Sticht
Navy Personnel R&D Center
San Diego, CA 92152

Dr. David Stone
KAJ Software, Inc.
3420 East Shea Blvd.
Suite 161
Phoenix, AZ 85028

Cdr Michael Suman, PD 303
Naval Training Equipment Center
Code N51, Comptroller
Orlando, FL 32813

Dr. Hariharan Swaminathan
Laboratory of Psychometric and
Evaluation Research
School of Education
University of Massachusetts
Amherst, MA 01003

Mr. Brad Sympson
Navy Personnel R&D Center
San Diego, CA 92152

Dr. John Tangney
AFOSR/NL
Bolling AFB, DC 20332

Dr. Kikumi Tatsuoka
CERL
252 Engineering Research
Laboratory
Urbana, IL 61801

Dr. Maurice Tatsuoka
220 Education Bldg
1310 S. Sixth St.
Champaign, IL 61820

Dr. Martin M. Taylor
DCIEM
Box 2000
Downsview, Ontario
CANADA

Dr. Perry W. Thorndyke
FMC Corporation
Central Engineering Labs
1185 Coleman Avenue, Box 580
Santa Clara, CA 95052

Major Jack Thorpe
DARPA
1400 Wilson Blvd.
Arlington, VA 22209

Dr. Martin A. Tolcott
3001 Veazey Terr., N.W.
Apt. 1617
Washington, DC 20008

Dr. Douglas Towne
Behavioral Technology Labs
1845 S. Elena Ave.
Redondo Beach, CA 90277

Dr. Robert Tsutakawa
Department of Statistics
University of Missouri
Columbia, MO 65201

Dr. David Vale
Assessment Systems Corp.
2233 University Avenue
Suite 310
St. Paul, MN 55114

Dr. Kurt Van Lehn
Xerox PARC
3333 Coyote Hill Road
Palo Alto, CA 94304

Dr. Beth Warren
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Roger Weissinger-Baylon
Department of Administrative
Sciences
Naval Postgraduate School
Monterey, CA 93940

Dr. Donald Weitzman
MITRE
1820 Dolley Madison Blvd.
MacLean, VA 22102

Dr. Shih-Sung Wen
Jackson State University
1325 J. R. Lynch Street
Jackson, MS 39217

Dr. Keith T. Wescourt
FMC Corporation
Central Engineering Labs
1185 Coleman Ave., Box 580
Santa Clara, CA 95052

Dr. Douglas Wetzel
Code 12
Navy Personnel R&D Center
San Diego, CA 92152

Dr. Mike Williams
IntelliGenetics
124 University Avenue
Palo Alto, CA 94301

Dr. Hilda Wing
Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

Dr. Robert A. Wisher
U.S. Army Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Martin F. Wiskoff
Navy Personnel R & D Center
San Diego, CA 92152

Dr. Frank Withrow
U. S. Office of Education
400 Maryland Ave. SW
Washington, DC 20202

Mr. John H. Wolfe
Navy Personnel R&D Center
San Diego, CA 92152

Dr. George Wong
Biostatistics Laboratory
Memorial Sloan-Kettering
Cancer Center
1275 York Avenue
New York, NY 10021

Dr. Wallace Wulfeck, III
Navy Personnel R&D Center
San Diego, CA 92152

Dr. Joe Yasatuke
AFHRL/LRT
Lowry AFB, CO 80230

Major Frank Yohannan, USMC
Headquarters, Marine Corps
(Code MPI-20)
Washington, DC 20380

Mr. Carl York
System Development Foundation
181 Lytton Avenue
Suite 210
Palo Alto, CA 94301

Dr. Joseph L. Young
Memory & Cognitive
Processes
National Science Foundation
Washington, DC 20550

Cmdr. Joe Young
HQ, MEPCOM
ATTN: MEPCT-P
2500 Green Bay Road
North Chicago, IL 60064

Dr. Steven Zornetzer
Office of Naval Research
Code 440
800 N. Quincy St.
Arlington, VA 22217-5000